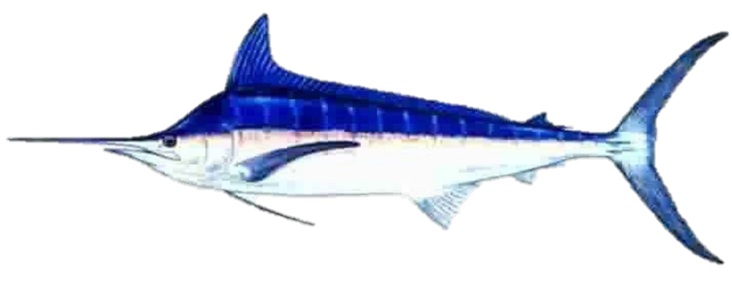
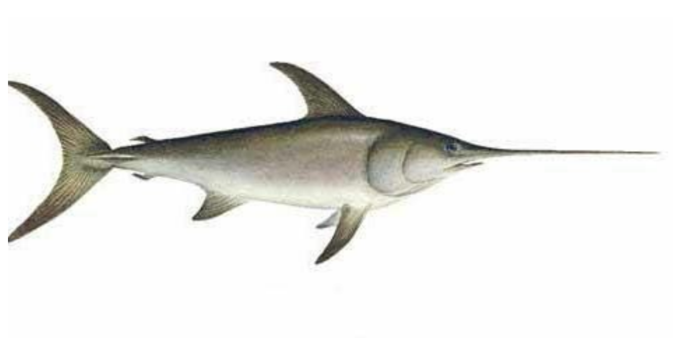
Standardized catch rates of blue marlin (*Makaira nigricans*) in the Hawaii-based longline fishery (1995-2014)[1]

Felipe Carvalho[1, 2], Willian Walsh[1, 2], and Yi-Jay Chang[1, 2]

[1]Joint Institute for Marine and Atmospheric Research University of Hawaii
Honolulu, Hawaii, USA, 96822
[2]NOAA NMFS Pacific Islands Fisheries Science Center Honolulu, Hawaii, USA, 96816





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Abstract

Integrated stock assessment models have been used by ISC to evaluate the status of the Pacific blue marlin *Makaira nigricans* population and to provide a basis for management advice. These models require a standardized index of relative abundance, such as CPUE. This working paper presents a standardized CPUE series for blue marlin caught in the deep-set sector of the Hawaii-based pelagic longline fishery in 1995–2014 using data from the Pacific Islands Regional Observer Program (PIROP). CPUE was standardized with Generalized Linear Models (GLMs). The best fitting models were selected on the basis of its Akaike Information Criterion (AIC). As in previous analyses, predicted CPUE showed downward trends early in the time series followed by rough stability since 2002.

Introduction

Blue marlin, the most tropical of the istiophorid billfishes (Nakamura 2001), is believed to comprise a single stock in the Pacific Ocean (Graves and McDowell 2003). This species can attain great size (Heemstra 1986; Nakamura 2001), with the largest females reaching 900 kg. This species is retained for human consumption in many locales (Nakamura 2001) including Hawaii. Blue marlin is an apex predator, but ecological simulations suggest that it could recover relatively quickly after removal of fishing mortality (Kitchell et al. 2005).

There are no directed commercial fisheries for Pacific blue marlin in Hawaii, however, it is often caught as a bycatch in the Hawaii-based pelagic longline fishery. Blue marlin comprised 5% of all captured billfishes reported by fishery observers in 1995–2014. A stock assessment for blue marlin was conducted in 2013 under the auspices of the ISC Billfish Working Group (BILLWG). The assessment indicates that the Pacific blue marlin stock is currently not overfished and is not subject to overfishing relative to MSY-based reference points

Fishery stock assessment, such as the one conducted for the Pacific blue marlin, requires a time series of an index of abundance that is proportional to stock size. These can be provided from fishery catch-per-unit of effort (CPUE). The simple linear model often used to describe the relationship between abundance (N) and the relative abundance index (I) in t^{th} year is $I_t =$

$q_t N^t$, where q is the catchability coefficient. In this case if catchability remains the same over time, CPUE does vary with biomass, and is a good index. However, if catchability changes over-time our key assumption in stock assessment that CPUE will vary proportionally with stock size is no longer true. Many factors can affect CPUE, such as season, area, gear configuration, targeting strategy, environmental factors, among others. Consequently, in most cases, nominal CPUEs are of little value as they do not express the actual abundance of the exploited stock. A common way to account for such influences is to use Generalized Linear Models (GLM) to standardize CPUE series.

In preparation for the next blue marlin stock assessment in 2016 this working paper (WP) presents a standardized catch-per-unit-effort (CPUE) for blue marlin in the Hawaii-based pelagic longline fishery in 1995–2014, the models used here were an update from those presented in Walsh et al. (2013).

Materials and methods

Fishery data

The data used for this study was collected by fishery observers' onboard Hawaii-based pelagic longline vessels, and included species-specific catch and information on operational (e.g., geographical position of longline sets, number of hooks deployed, set and haul times) descriptors from each longline set (Pacific Islands Regional Office, 2009). The SST data were weekly mean values measured by an advanced, very high resolution radiometer borne by a NOAA satellite (Walsh et al., 2007). Catches, fishing effort (i.e., numbers of hooks), catches per longline set, and nominal CPUE are tabulated by fishery sectors, calendar quarters, and fishing regions. The two fishery sectors are separated in shallow-set and deep-set, and were defined according Federal Register (Department of Commerce, 2004). Shallow-sets used < 15 hooks per float whereas deep-sets used ≥ 15 hooks per float (Walsh et al., 2009). There are no 2001-2004 shallow-set data because the fishery was closed from mid-March 2001 until April 2004, in addition to the closure, the shallow-set fishery was suspended in 2006, from mid-March through the end of the year, and again for the last several weeks of 2011. Fishing regions were divided into eight regions, based on Walsh and Teo (2012). Due to the closure of the shallow-set and the large majority (86%) of blue marlin catches come from the deep-set fishery sector, this WP presents the CPUE standardization for the deep-sector only.

Data exploration

Nominal CPUE was analyzed in terms of shape with a histogram, and tested for normality with a Kolmogorov–Smirnov test with Lilliefors correction. The candidate continuous explanatory variables were analyzed with correlation matrices plots and by calculating non-parametric Spearman correlation coefficients. Those plots and correlation tests were mainly used for a preliminary analysis between the response variable and the candidate explanatory variables, as well as for eventual correlations between the explanatory variables. For the relationships between the response variable and the candidate categorical explanatory variables, boxplots and nonparametric tests were used to assess if differences occurred in the blue marlin CPUE of the various categories of these variables. These procedures were conducted using the *cor.test* function in the STATS library in R.

Statistical modeling

Standardizations were performed for blue marlin catch and effort data using GLM. The number of zero blue marlin catches was relatively high (82%). As these zeros can cause mathematical problems for fitting the models, two different approaches were tested and compared: delta-lognormal (DLN) and zero-inflated negative binomial (ZINB). The DLN analyzes separately the positive observations and the probability that a null or positive observation occurs, and consists of two GLM which respectively use a lognormal and a binomial distribution. The logarithm of the CPUE is the response variable in the lognormal model and the identity is the link function. The proportion of positive captures is the response variable in the Binomial Model and the link function is the logit. Zero-inflated models are capable of dealing with excess zero counts. In essence, they can be interpreted as a two-component mixture model combining a point mass at zero with a count distribution such as negative binomial. The model divides the population into two groups: one group for which the outcome is always zero and one group for which the outcome is drawn from the underlying count data distribution. Each explanatory variable can have an effect on either or both the probability that an individual belongs to the "always zero group" and the magnitude of the count outcome, given that the individual belongs to the "not always zero group".

The candidate factor variables followed the previous work from Walsh et al. (2013), and included the years, calendar quarters, eight fishing regions, and six bait types. The candidate continuous variables included the sea-surface temperature (SST; °C), the vessel length (ft), and the begin-set time (HST). Interactions between year and quarter, region and quarter, were also added. The models were fitted by forward selection stepwise based on Akaike Information Criterion (AIC) (Akaike 1973). At each step in the model selection procedure, the factor that resulted in the greatest reduction in AIC from the model in the previous step was added to the model. The contribution of each variable to the reduction of AIC and explanation of deviance from the null model were also provided to determine importance of each variable. Model diagnostics was based on residual analysis. Pearson residuals were plotted against fitted values and against each explanatory variable in the final model. A histogram of residuals was used to assess normality for all models, in addition a quantile-quantile normal probability plot for the positive process of the DLN.

An index of relative abundance was calculated for each distribution. The standardized CPUE index and its variance were calculated as the mean and variance, respectively, of the predicted values on the scale of the response in each year using the "predict" function in R. The variance of the delta-lognormal distribution was calculated as the Taylor series expansion of the variance of the product of two independent random variables (Brodziak and Walsh, 2013; Eq. 7). Bias-correction was applied when back-transforming the positive process of the DLN model from ln(CPUE) to CPUE.

All statistical analyses for this paper were carried out with the R Project for Statistical Computing version 3.1.0 (R Core Team, 2013).

Results

The total observed catch was 12,828 blue marlin. These fish were taken on 50,716 observed deep-sets from January 1995 through December 2014. The mean (±SD) nominal catch per set and CPUE were 0.12±0.34 per 1000 hooks. For the zero process in the final selected DLN model the variables that contributed for explaining part of the deviance included: years, quarters, fishing regions, SST, bait types, and interactions years:quarters and quarter:regions (Table 1). The variables selected explained 14.1% of the null deviance. Quantile residual plots showed normality in the distribution of the residuals and no patterns within variables (Figure 1). For the positive process in the final selected DLN model SST was the only variable not selected (Table 1). The variables selected explained 25% of the null deviance. Pearson residual plots for the positive process showed some skewness in the distribution of the residuals, and patterns within the variables (Figure 2).

For the count process in the best ZINB model all variables were selected, however the best model for the zero process consisted of variables years, SST, Vessel length, and bait types (Table 2). Several attempts to fit a zeros model with additional variables did not converge. Pearson residual plots showed some skewness in the distribution of the residuals, and patterns within the variables (Figure 3).

The standardized blue marlin CPUE between 1995 and 2014 for both DLN and ZINB models were very similar (Figure 4, Table 3), they showed a general downward trend in the early time series, stabilizing around 2002. The standardized indices of CPUE were similar to the nominal index (Figure 4).

Discussion

The similar patterns of the standardized CPUE indices produced by the DLN and ZINB models suggested that the overall trend in blue marlin CPUE was robust to the choice of distribution. Results showed here are consistent with those obtained by Walsh et al. (2013). Consequently, we recommend that the existing ZINB methodology for standardizing blue marlin CPUE for the Hawaii longline fishery be maintained for the stock assessment update.

References

Brodziak, J. and W.A. Walsh. 2013. Model selection and multimodel inference for standardizing catch rates of bycatch species: a case study of oceanic whitetip shark in the Hawaii-based longline fishery. Can. J. Fish. Aquat. Sci. 70:1723-1740.

Graves, J.E. and J.R. McDowell. 2003. Stock structure of the world's istiophorid billfishes: a genetic perspective. Marine and Freshwater Research 54:287–298.

Heemstra, P.C. 1986. Family No. 252: Istiophoridae. Sailfish, spearfishes and marlins. *in* Smiths' Sea Fishes. Edited by: M.M. Smith and P.C. Heemstra. Springer-Verlag. Berlin.

Kitchell, J.F., S.J.D. Martell, C.J. Walters, O.P. Jensen, I.C. Kaplan, J. Watters, T.E. Essington, and C.H. Boggs. 2006. Billfishes in an ecosystem context. Bulletin of Marine Science 79: 669–682.

Nakamura, I. 2001. Istiophoridae: Billfishes. *in* The Living Marine Resources of the Western Central Pacific. Volume 6. Bony Fishes Part 4 (Labridae to Latimeriidae), estuarine crocodiles, sea turtles, sea snakes and marine mammals. Edited by: K.E. Carpenter and V.H. Niem. FAO. Rome.

Pacific Islands Regional Office. 2009. Hawaii Longline Observer Program Observer Field Manual. Version LM.09.11. National Oceanic and Atmospheric Administration, Pacific Islands Region, Honolulu, Hawaii.

R Core Team. 2014. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL http://www.R-project.org/.

Walsh, W. A., K. A. Bigelow, and R. Y. Ito. 2007. Corrected catch histories and logbook accuracy for billfishes (Istiophoridae) in the Hawaii-based longline fishery. NOAA Technical Memorandum NMFS-PIFSC-13.

Walsh, W.A., K.A. Bigelow, and K.L. Sender. 2009. Decreases in shark catches and mortality in the Hawaii-based longline fishery as documented by fishery observers. Marine and Coastal Fisheries: Dynamics, Management, and Ecosystem Science 1:270–282.

Walsh, W. A., and Teo, S. L. H. 2012. Catch statistics, length data, and standardized CPUE for blue shark *Prionace glauca* taken by longline fisheries in Hawaii and California. ISC/12/SHARKWG-1/02 (working paper).

Walsh, W. A., Chang, Y., Lee, H. 2013. Catch Statistics, Size Compositions, and CPUE Standardizations for Blue Marlin *Makaira nigricans* in the Hawaii-based Pelagic Longline Fishery in 1995-2011. ISC/13/SHARKWG-1/03 (working paper).

Table 1. Df = the degrees of freedom, ΔAIC = the reduction in AIC, and the explanation of null deviance overall and per degrees of freedom for the components of the delta-lognormal model when each variable selected in the best model was added to the null model.

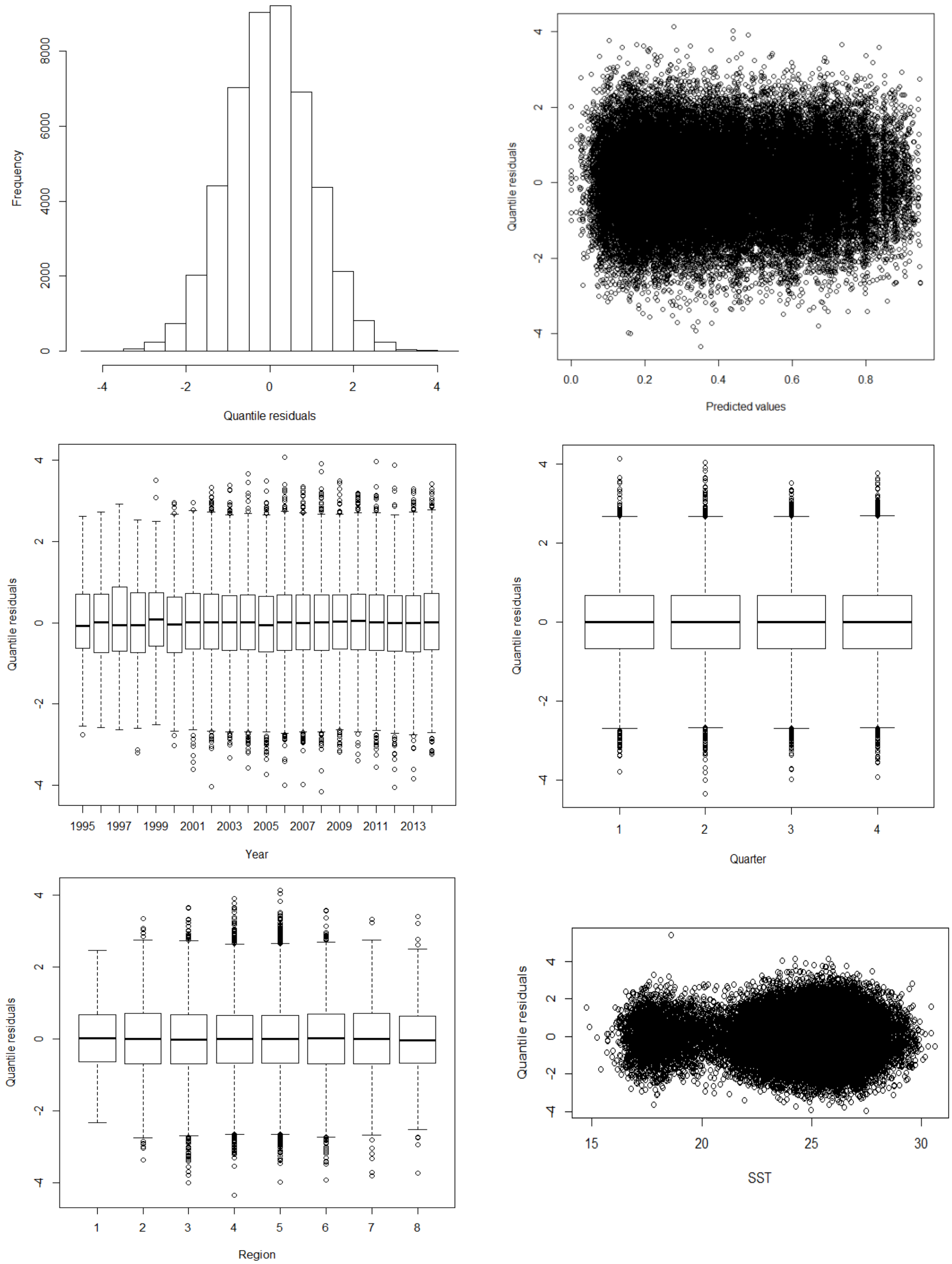
Delta-Lognormal				
Variable	Df	ΔAIC	Explanation of null deviance	ΔDeviance reduced per df
Zero process				
Years	19	877.1	2.2%	46.16
Quarters	3	1186.3	2.9%	395.4
Regions	7	2877.5	7.1%	411.1
Bait types	6	164.2	0.4%	27.3
SST	1	463.7	1.2%	463.7
Years:Quarters	57	201.8	0.7%	3.5
Regions:Quarters	21	159.2	0.5%	7.6
Positive process				
Years	19	1943.2	16.4%	102.2
Quarters	3	481.3	4.2%	160.4
Regions	7	534.7	5.1%	76.4
Bait types	6	280.1	1.4%	46.7
Vessel length	1	72.8	0.4%	72.8
Years:Quarters	57	117.6	0.9%	2.0
Regions:Quarters	21	115.3	0.8%	5.5

Table 2. df = the degrees of freedom, ΔAIC = the reduction in AIC, % ΔAIC = the percentage reduction in AIC from the null model, and % ΔAIC per df = the reduction in AIC per degrees of freedom for the zero and count components of the zero inflated negative binomial model when each variable selected in the best model was added to the null model.

Zero inflated Negative Binomial			
Variable	Df	ΔAIC	ΔAIC per df
Zero process			
Years	18	121.7	6.7
SST	1	42.3	42.3
Bait types	6	21.9	3.6
Vessel length	1	28.4	28.4
Count process			
Years	18	974.2	54.1
Quarters	3	1302.1	433.7
Regions	7	4083.5	583.3
Bait types	6	212.1	35.3
SST	1	817.6	817.6
Years:Quarters	57	367.1	6.4
Regions:Quarters	21	248.7	11.8

Table 3: Standardized CPUE indices and coefficient of the variations (CV) for the best model for the delta-lognormal (DLN), and zero-inflated negative binomial (ZINB), and the distributions from the deep-set data only.

	Index		CV	
Year	ZINB	DLN	ZINB	DLN
1995	0.51	0.49	0.79	0.51
1996	0.57	0.41	0.78	0.53
1997	0.48	0.36	0.72	0.48
1998	0.47	0.28	0.81	0.49
1999	0.14	0.16	0.67	0.37
2000	0.45	0.26	0.53	0.41
2001	0.30	0.18	0.48	0.35
2002	0.14	0.13	0.54	0.46
2003	0.23	0.15	0.61	0.41
2004	0.17	0.13	0.47	0.39
2005	0.12	0.13	0.53	0.38
2006	0.23	0.13	0.62	0.41
2007	0.05	0.07	0.55	0.39
2008	0.12	0.10	0.49	0.47
2009	0.11	0.10	0.52	0.37
2010	0.07	0.08	0.51	0.35
2011	0.10	0.09	0.48	0.46
2012	0.16	0.11	0.67	0.38
2013	0.07	0.10	0.49	0.46
2014	0.11	0.11	0.46	0.51



Frequency
Quantile residuals
Predicted values
Quantile residuals
Year
Quantile residuals
Quarter
Quantile residuals
Region
Quantile residuals
SST

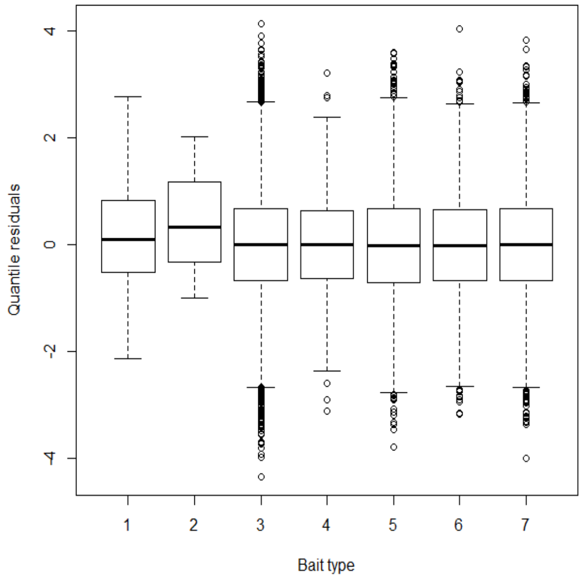
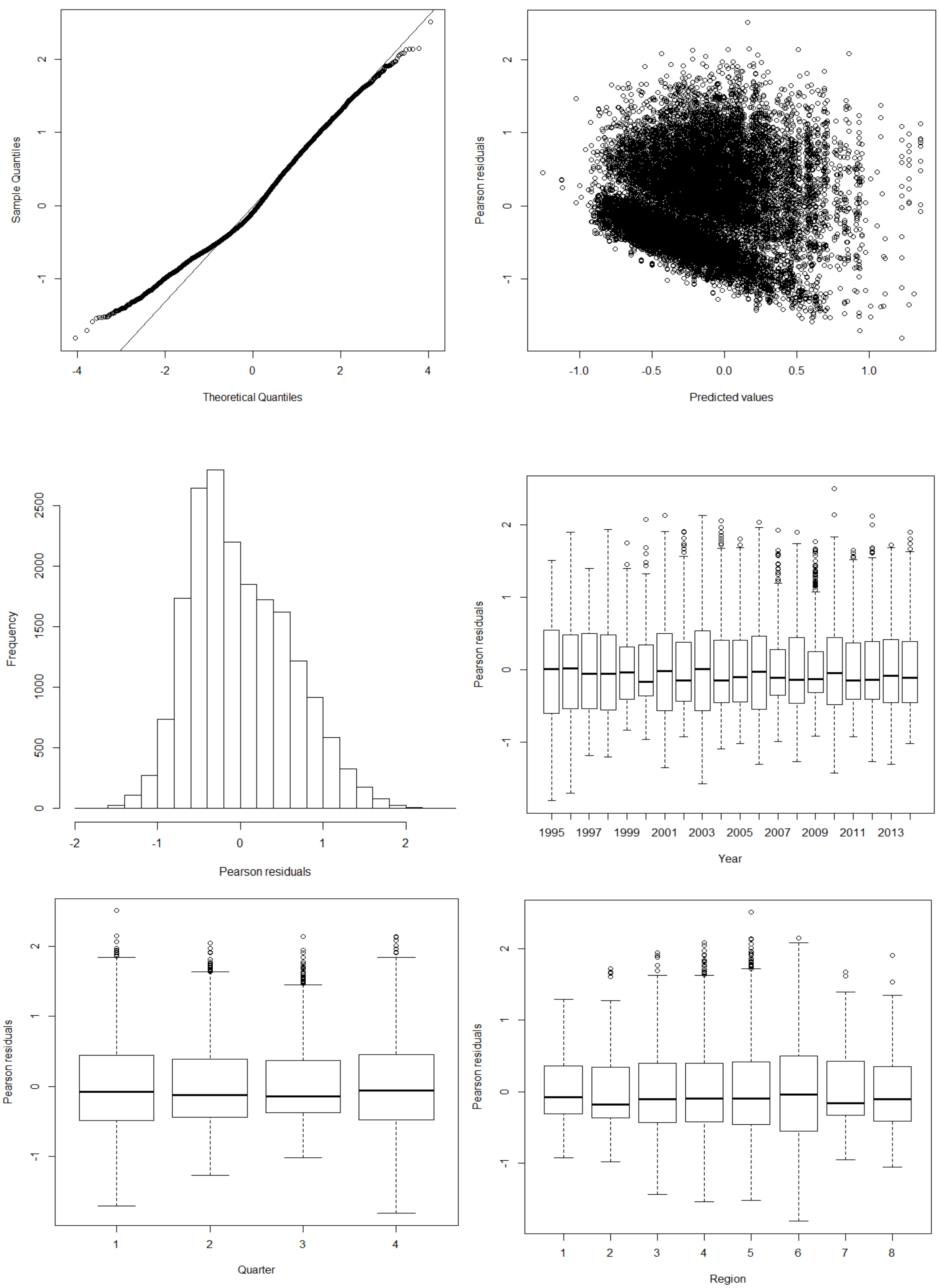


Figure 1. Quantile residual plots for the zero process of the delta-lognormal distribution from the deep-set data only.


Sample Quantiles
Theoretical Quantiles
Pearson residuals
Predicted values
Frequency
Pearson residuals
Pearson residuals
1995 1997 1999 2001 2003 2005 2007 2009 2011 2013
Year
Pearson residuals
Quarter
Pearson residuals
Region

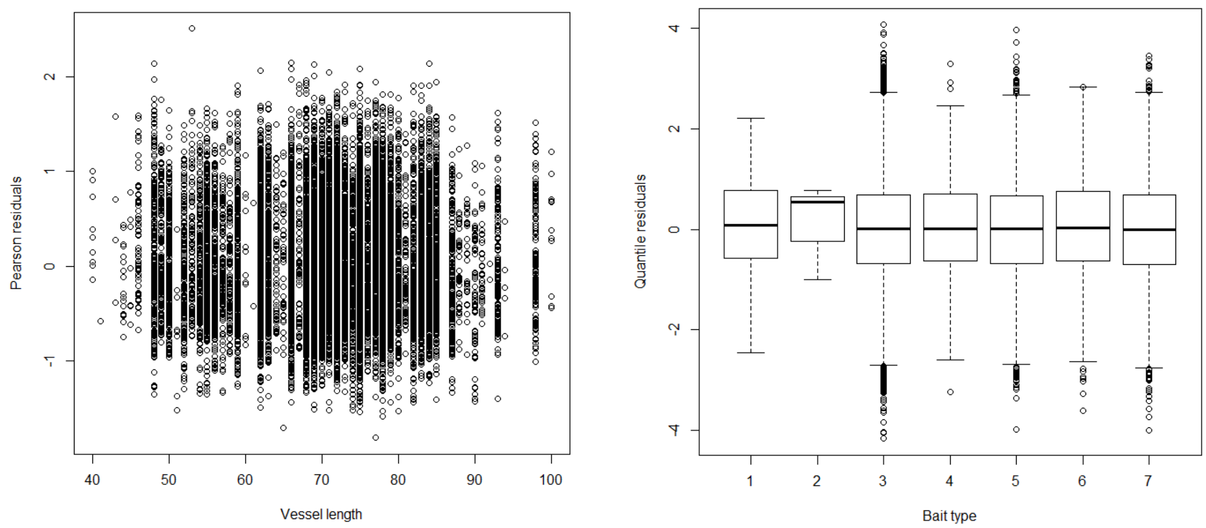
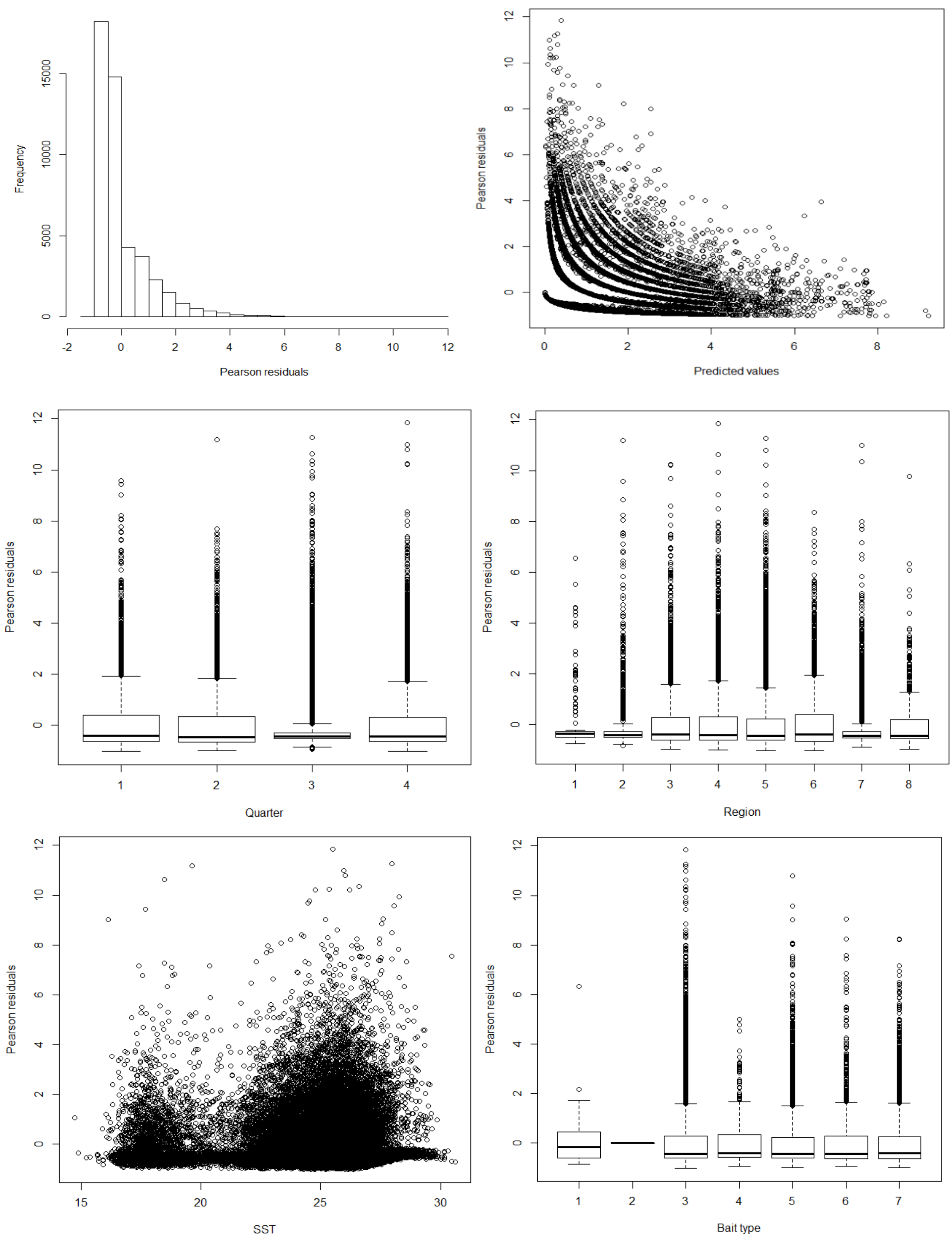


Figure 2. Quantile residual plots for the count process of the delta-lognormal distribution from the deep-set data only.



Frequency
Pearson residuals
Predicted values
Pearson residuals
Quarter
Pearson residuals
Region
Pearson residuals
SST
Pearson residuals
Bait type

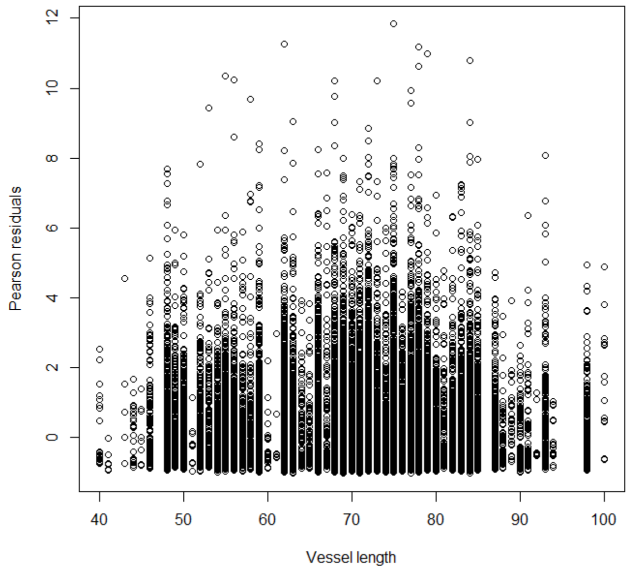


Figure 3. Pearson residual plots for the zero-inflated negative binomial from the deep-set data only.

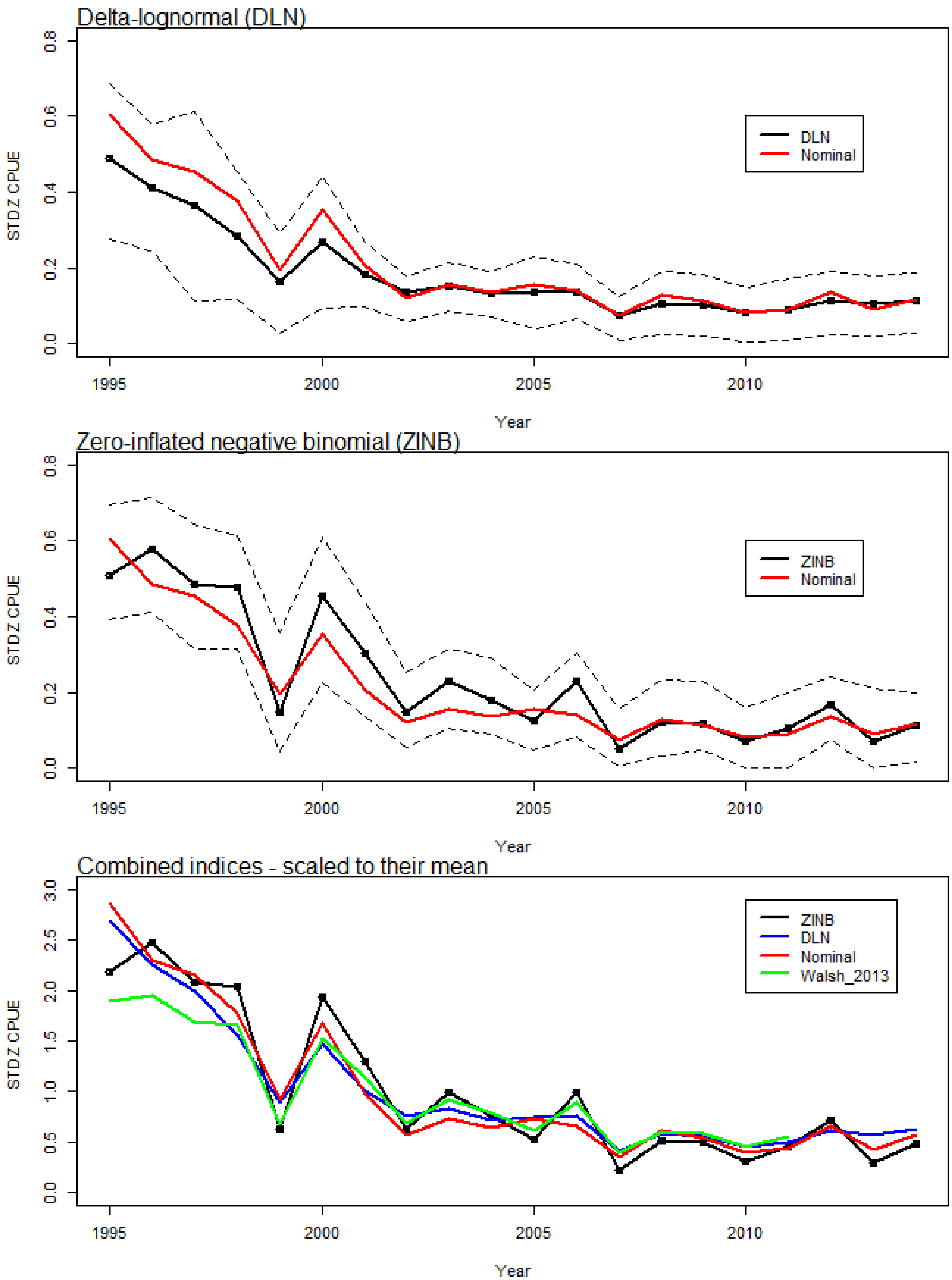


Figure 4. Standardized index from the delta-lognormal (DLN), and the zero-inflated negative binomial (ZINB) with +/- one standard deviation (dashed lines).